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Influence of Intersection Density on Risk Perception of Drivers in Rural Roadways: A Driving Simulator Study

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Abstract: With the aim of maintaining a decent level of accessibility, the presence of intersections, often in high numbers, is one of the typical features of rural roads. However, evidence from literature shows that increasing intersection density increases the risk of accidents. Accident analysis literature regarding intersection density primarily consists of accident prediction models which are a useful tool for measuring safety performance of roads, but the literature is lacking in terms of evaluation of driver behavior using direct measurements of driver performance. This study focuses on the influence of intersection density on the risk perception of drivers through experiments carried out with a driving simulator. A virtual driving environment of a rural roadway was constructed. The road consisted of segments featuring extra-urban and village driving environments with varying intersection density level. Participants were recruited to drive through this virtual driving environment. Various driver performance measures such as vehicle speed and brake and gas pedal usage were collected from the experiment and then processed for further analysis. Results indicate an increase in driver's perceived risk when the intersection density increased, according with the findings from the accident prediction modeling literature. However, at the same time, this driving simulator study revealed some interesting insights about oscillating perceived risk among drivers in the case of mid-level intersection separation distances. Beyond the accident research domain, findings from this study can also be useful for engineers and transportation agencies associated with access management to make more informed decisions.

Keywords: driving simulator; intersection density; driver's risk perception; rural roads; sustainable transportation

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1. Introduction

The increasing level of injuries and deaths resulting from the road accidents has made road safety issues one of the major global concerns. According to the World Health Organization (WHO), deaths resulting from road accidents are the world's 8th leading cause of death, causing nearly 1.35 million deaths per year [1]. Fatalities on rural roads are a major part of this global road safety problem. According to an international transport forum, most road fatalities occur on rural roads in International Traffic Safety Data and Analysis Group (IRTAD) member countries. Among IRTAD member countries, road fatalities on rural roads represented between almost 40% (in Portugal) and 76% (in New Zealand) of all road accident deaths. In Italy, the analysis of fatalities by road type shows that the rural network is the deadliest: 48% of death occurred on rural roads, 42% on urban roads, and 10% on motorways. Together with driving under the influence of alcohol and/or drugs, distraction, inappropriate and excessive speed, lack of physical separation, inadequate roadside, and presence of numerous intersections are considered the major causes of accidents on rural road [2].

The EU is no exception to this trend. According to CARE (Community database on road accidents resulting in death or injury—DG move—EU Commission), in the EU the 52% of the total accidents recorded in 2019 took place on rural roads. Among the EU member states, this statistic varied from 17.0% to 77.7%, in Italy the number was 48.3%. On rural roads intersections, particularly the ones at grade, have a significant responsibility for road accidents. According to [3], in 2019, in Italy most accidents occurred in at-grade junctions, followed by 44% on crossroads (4 arms), and the remaining (6%) on roundabouts. The roundabouts have strongly contributed to improving safety, thanks to their various advantages, such as a small number of collision points compared to other types of intersections, speed reduction when crossing the intersection, and low loss of time for drivers at inlets [4–6].

Globally, rural roads are absolutely vital for connecting small towns and settlements with big towns and cities. Aimed at maintaining a decent level of accessibility, the presence of intersections, often in high numbers, is one of the typical features of rural roads, but evidence from the literature suggests that this feature increases the risk of accidents.

Several studies confirm the responsibility of at-grade intersections, identifying the relationships between the number of junctions and generic malfunctioning such as traffic congestion and accidents. In particular, a study by Gluck and Levinson [7] identified intersections as the main source of accidents and congestion. In another study, Miaou and Lum [8] showed that direct accesses in a road may cause a significant increase in accidents.

In harmony with the findings of these studies, various access management manuals developed by transport agencies throughout the world and in the manual published by the Transportation Research Board (TRB), William et al. [9] identified access density as one of the most important factors that influences occurrence of accidents and suggested a series of access control techniques to improve road safety levels. In this regard, the Highway Safety Manual (HSM) contains Safety Performance Functions (SPFs), Crash Modification Factors (CMFs), and Calibration Factors to numerally quantify the effects [10].

Many studies have developed SPFs for rural two-lane roadways [11,12]. However, the SPFs given in the HSM for intersections only estimate total crashes, which might not be an ideal approach since crashes vary by type and severity across intersections [11,13,14].

Differences in the distribution of crash severity and/or crash type could be attributed to the variation in the geometric design and traffic characteristics between intersections. In order to consider those variations, studies estimate predictive models for intersections by crash type [15–19], and/or by severity level [14,16,20,21].

Furthermore, quite a few studies have been carried out with some form of model developed from the accident data, e.g., [22–30]. The majority of these studies were carried out by calculating the relationships between the accidents and the presence of conditions relevant to the junction, the access density is the most important. Almost all the studies pointed out a correlation between the junction density and the expected ratio of accident.

Recently, Elvik [31] carried out a meta-analysis on the available coefficient for the access density and found an estimated value of 0.039, and therefore in the study, he concludes that the accident rate increases by about 4% when the number of accesses on the road increases by one per kilometer.

Historical accident data were used to develop and calibrate different statistical models. Some of them make use of a simple model such as multiple linear regression, which hypothesizes normally distributed errors [25]. However, they quickly realized that this technique has limitations. Normal distribution is not ideal to model the occurrence of accidents as long as road accidents are casual and rare events [32]. Even the number of expected accidents can be negative when a general linear regression model [33] is used.

Many researchers began to prefer the Poisson regression model, a type of counting model based on a general linear structure with respect to the regression models based on conventional multiple linear regression. The literature on the analysis of accident data records several studies carried out with Poisson regression to explore the relationship between the occurrences and the accident frequency [34–37]. Later, Lord and Manning [38] noticed that the Poisson regression model often shows an excessive dispersion, thus Negative Binomial (NB) distribution is more appropriate. An increasing number of studies on accident data modeling make use of the Generalized Linear Modeling (GLM) with a NB generalized structure of the error [28,39–42].

Driving is a complex information processing task. Many behavioral and non-behavioral factors influence driver performance. Hence, relying only on historical accident data for understanding the safety effects of potential determinants of accidents is not enough. For this reason, in accident predictive models, it is necessary to evaluate driver behavior using measurements of driver performance.

In recent decades, researchers have tried to use driving simulators to overcome this issue by studying driver behavior by collecting data on driver performance measures such as speed, braking behavior, acceleration pattern, etc. These measures are indicators of drivers' risk perception and therefore, by studying these measures, it is possible to identify the driving situations that can potentially lead to accidents, and eventually road fatalities. Although drivers' risk perception has been studied using driving simulators with respect to different traffic events and road geometry [43], no driving simulator study has been found that focuses on the analysis of driver behavior with respect to intersection density. Some related studies that used driving simulator for access- or intersection-related research have been carried out. Yan et al. [44] investigated if the driving simulator can be used as a valid tool to assess road safety at signalized intersections. They used traffic parameters such as speed and surrogate safety measures such as crash history record, deceleration rate, non-stop right-turn rate on red, and following distance. In another study, Dixon and Brown [45] assessed drivers' reactions to driveway activity using perception reaction time, speed reduction, and deceleration rate. De Blasiis et al. [46] used a driving simulator to show variability in terms of drivers' behavior depending on the speed of approach in the weaving lane. A driving simulator was used in another study [47] to demonstrate that the increase of weaving lane length is effective only when the traffic flow conditions exceed a certain threshold.

Keeping in mind the issue of drivers' risk perception related to intersection density, in this paper, a novel effort was made using a driving simulator as a tool for the investigation of the influence of intersection density levels on a driver's risk perception by collecting data on driver performance. This paper is organized as follows: the first section introduces the problem, research needs, and objectives; the second section discusses the experimental tests in virtual reality, designed to analyze the correlation between intersection distances and drivers' risk perception; the third section presents the analyses of the indicators and the results of the elaborations; the fourth part discusses the results referring in particular to the relationship between speed and risk perception. The final section presents conclusions and recommendations.

2. Materials and Methods

A virtual driving environment was created in a full-scale high fidelity driving simulator. Drivers were recruited to drive in that virtual environment in order to collect data on driver performance. The data were extracted and processed to analyze driver behavior in presence of different levels of intersection density. The advantage of the driving simulator is that it allows the researchers to collect real-time driving performance behavior in a controlled and repeatable environment. This repeatability helps to collect data for each driver in the same scenario.

2.1. Description of the Simulator

The research was carried out using the LassTRE (Laboratory of road safety of Roma Tre University) virtual reality driving simulator located at the Department of Engineering of the Roma Tre University. It is a fixed base driving simulator, shown in Figure 1.

Figure 1. LassTRE virtual reality driving simulator.

The simulator is equipped with a driving simulation software called STISIM Drive. The reliability of this driving simulator as a tool has been fully validated by several studies [48]. From the hardware point of view, the simulator is a real vehicle, a Toyota Auris, converted to a driving simulator by removing all unnecessary parts and integrating the vehicle with the components that communicate with the workstation, equipped with the software STISIM Drive. The system is also equipped with high-definition projectors that project the scenarios in front of the car and sideways on a curved projection screen that covers a visual angle of 135°. Furthermore, there are sound speakers which are located in the hood of the car in order to emulate the acoustic environment.

2.2. Scenario Design

A virtual driving environment representative of a standard two-way two-lane rural road was created using STISIM scenario definition language. The entire driving track was an undivided two-way two-lane rural road with lane width of 3.5 m and 1.25 m of shoulder width (out of which 0.12 m was of lane marking). These values are representative of the dimensions of rural roads as noted by different researchers in the literature. The total length of the simulated driving track was 28.1 km. Intersection density varied across different segments of the road. Four intersection density levels were introduced in the road. In other words, four different levels of distance between two successive intersections were used for this study. These distances were 100 m, 200 m, 300 m, and 600 m. Intersections were located in straight sections and flat altimetric conditions so that the driver, for the intersections located at distances of 100 m and 200 m, could see at least two in succession, both in the villages and in the suburban area. For the intersections located at a distance of 300 m and 600 m, instead, as required by Italian regulation, the warning was only due to the signs. Similar to a usual natural rural road driving environment, the simulator track passed through three small villages along its way. Table 1 shows the scheme of the virtual driving environment, the characteristics, and the total length of different segment of the road.

All the intersections introduced in the virtual driving environment were 90-degree intersections. Vehicles were introduced in the scenario to emulate a real-world-like driving environment. Some of the vehicles introduced in the scenario entered the road on which driver was driving using the intersections. Furthermore, 50% of the intersections were T intersections and the remaining 50% were X intersections. In addition, 80% of the intersections had a vehicle in them and the remaining 20% did not have any vehicle. In the X intersections with vehicles, the ratio of vehicles in both legs and vehicles in one leg was 50:50 for villages and 20:80 for extra-urban areas. However, not all of the vehicles present at the intersections entered the road: 50% of the vehicles at the T intersections entered the road. For vehicles at X intersections, 40% entered the road, 20% crossed the road. Three different levels of temporal gaps (5, 7, and 10 s for 70%, 20%, and 10% vehicles, respectively) were used for the vehicles entering the road. These different levels of temporal gaps are representative of the presence of drivers with different risk-taking mentality levels in the actual roads. Location, type of intersections, and vehicles were introduced randomly.

Table 1. Summary of segments.

Segment No.	Start (km Mark)	End (km Mark)	Distance between Successive Intersections (m)	Type
1	0	0.5	200	Extra-urban
2	0.5	1.5	100	Village
3	1.5	2.5	300	Extra-urban
4	2.5	3.5	without intersections	Extra-urban
5	3.5	6.5	300	Village
6	6.5	7.5	100	Extra-urban
7	7.5	9.6	200	Extra-urban
8	9.6	10.6	without intersections	Extra-urban
9	10.6	12.6	600	Extra-urban
10	12.6	13.6	100	Village
11	13.6	17.8	300	Extra-urban
12	17.8	18.8	600	Extra-urban
13	18.8	20.9	200	Extra-urban
14	20.9	25.1	100	Extra-urban
15	25.1	26.1	without intersections	Extra-urban

2.3. Data Collection

A homogeneous sample of 38 subjects, 18 women and 20 men, 38 years old on average (age range 25–50) was recruited as volunteers from the Department of Engineering at Roma Tre University. All participants had a valid Italian driving license and reported having driven, on average, 10,000 km per year. None of the subjects had previous experience with a driving simulator.

At the beginning, they were informed about the procedure of the test in terms of duration, use of drivers' controls, and knowledge of the tool. They completed a questionnaire with personal information and were requested to complete a training scenario for at least 10 min in order to get confident with the tool. In order to select a homogenous sample of drivers to avoid biasing of the results induced by driver attitude, experience, age, and gender or other neuro-cognitive factors [49], a statistical criterion was applied.

In the sample, four persons felt nausea and dizziness due to the simulator and hence could not complete the drive. Data were collected for the remaining 34 persons. In order to test for the outliers, Chauvenet's criterion and Modified Thompson Tau test were performed on the average speed values in each of the 17 segments and average speed values for the entire track. Data corresponding to three drivers were identified and discarded as outliers. Therefore, the analysis was performed on the final data of 31 drivers. The technical capabilities of the STISIM driving simulator software allow to collect six data points per second. Each data point may contain a maximum of 40 variables.

In this study, various measures of driver performance were collected, in particular longitudinal speed, deceleration due to the brake, and acceleration due to the accelerator, intended as indicators of the driver's perception of risk.

It is reasonable to assume that the intersections could lead to a speed reduction. In fact, speed is one of the most reliable indices of driving risk levels [50], typically used to understand how the drivers perceive the road environment risks. In this regard, the average speed of each vehicle in different segments and the standard deviation values have been calculated and various statistical tests have been carried out.

The pressure on the brake pedal, measured in pounds, is an indicator that can give significant information about how the drivers perform the stopping maneuver after perceiving the obstacle [46]. If the driver slows down with a calibrated braking that does not require a high value of pressure on the brake pedal, it is possible to associate this behavior to a prudent behavior and a low risk perception. In contrast, a high value of pressure could correspond to a delayed or wrong scan of the risk, which requires a high pressure in order to stop before colliding. Similarly, during the acceleration, the risk perception was evaluated by the throttle pressure.

2.4. Data Analysis

After raw data were collected from the driving simulator using STISIM drive software, the data were recorded and processed so that further analysis could be carried out on the driver performance measures mentioned above. In case of comparison between two variable groups, first F tests for variances and then relevant *t* tests were performed. For the comparison among three or more variable groups, first the homogeneity of variances was checked and then if the homogeneity condition was met, the ANOVA (analysis of variance) and, as post hoc test, Tukey's honestly significant difference test were performed (Tukey's HSD, sometimes called Tukey–Kramer test for unequal sample sizes). Both of these tests analyze the differences among group means. However, the advantage of Tukey's HSD is that it helps to compare each pair of means. It is worth noting that for the comparison of multiple means, pairwise multiple *t* tests can be used but in that case, the type I error increases. Therefore, ANOVA and the post hoc Tukey's HSD test were employed here to compare pairs of multiple means. However, when the homogeneity of variance condition is not met, then the ANOVA was accompanied by two more tests, the Welch test and Brown–Forsythe test, to robustly check for any differences in means. In this case, as a post hoc test to perform pairwise comparison of means, the Games–Howell test was carried out.

3. Results

The aforementioned statistical tests were performed on the collected data of the driver performance measures one by one. In the following segments, graphical representation of the driver performance measures and the results of the statistical tests are shown along with the observations made based on them.

3.1. Average Speed in Different Segments

From the speed profile of the vehicle, the average speed of the vehicle in each distinct segment (in terms of intersection density) was calculated first for each participant separately and then an average for all participants was computed. Figure 2 and Table 2 show the average speed of the vehicle in different segments and various statistical tests done on them, respectively.

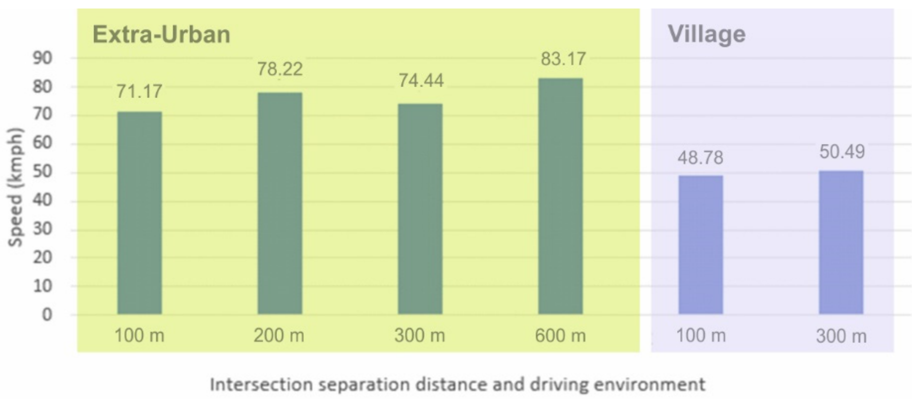

Figure 2. Average speed of the vehicle in each segment.

Table 2. Summary of the statistical tests done on average speed of the vehicle in each segment.

Extra-Urban Segments	Test Statistic	*p* Value
Test of homogeneity of variances	2.25	0.08
ANOVA	45.56	0.00
Tukey's HSD	$p < 0.05$ for all pairs	
Village Segments	**Test Statistic**	***p* Value**
F test for variances	2.306	0.01
t test assuming unequal variances	−1.662	0.05

It can be observed that for extra-urban segments, with increase in the distance between successive intersections or in other words with decrease in intersection density, the average speed in the segment increased with an exception for the case of 300 m. This departure from the trend was further explored by analyzing other driver performance measures. To ascertain if these differences in average speed values between different types of segments are statistically significant and not just a random occurrence, statistical tests were performed following the scheme mentioned before. The ANOVA test resulted in a *p* value of 0.00 and hence it implies that it is a statistically significant fact that the average speed values are not the same in different extra-urban segments with different intersection separation distances. Moreover, the *p* values from the Tukey's HSD test results showed that there exists a statistically significant difference among all the pairs.

3.2. Average Deceleration Due to Applied Brakes

Another important driver performance measure which is an indicator of driver's risk perception is the use of brakes. Brakes are used for reducing speed. It is the most widely taken action by drivers when they perceive any risk. Therefore, in this study, in addition to the speed values, pressure on the brake pedal was recorded in terms of longitudinal acceleration due to braking. Figure 3 shows the average acceleration of the vehicle due to braking in different types of segments (in terms of intersection density) of the road. It is worth noting that all the values are negative as these are actually deceleration values caused by braking.

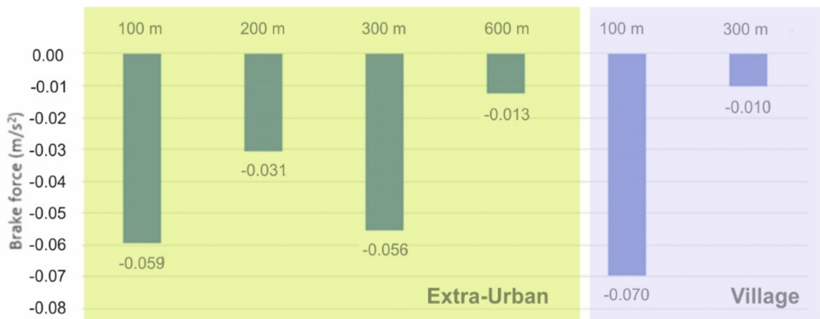

Figure 3. Average acceleration of the vehicle due to applied brakes in each distinct segment.

As explained earlier, STISIM records these deceleration values caused by braking for 6 times per second. The average of all such values within a segment was calculated. This value is also a representation of the total area under the deceleration curve in a segment. In harmony with the trend seen in the average speed figure above, it can be seen that with increasing intersection separation distance, the average deceleration decreased, but with an exception in the case of 300 m.

Table 3 shows that the ANOVA test, Welch test, and Brown–Forsythe all returned *p* values of 0.00, hence it is a statistically significant fact that the average brake force values are not the same in different extra-urban segments with different intersection separation distance. Moreover, the *p* values from the Games–Howell test that measures the significance show that there is a statistically significant difference among all the pairs, except the pair of intersection separation distances of 100 m and 300 m. Therefore, intersection separation distance or intersection density level influences the average brake force values or use of brakes in a rural road.

Table 3. Summary of the statistical tests done on average deceleration of the vehicle caused by braking in each segment.

Extra-Urban Segments	Test Statistic	*p* Value
Test of homogeneity of variances	2.25	0.08
ANOVA	45.56	0.00
Welch	29.59	0.00
Brown–Forsythe	17.89	0.00
Games–Howell	$p < 0.05$ for all pairs except one (100–300 m)	
Village Segments	**Test Statistic**	***p* Value**
F test for variances	3.560	0.00
t test assuming unequal variances	−6.800	0.00

Results from the *t* test (Table 3) show that the *p* value is less than 0.05 and hence it can be concluded that there is a statistically significant difference between the average brake force values between the segments within villages with different intersection separation distance.

3.3. Average Acceleration Due to Throttle

In addition to speed and brake force, throttle pressure or pressure on gas pedal is another important driver performance measure as an indicator of the driver's risk perception. This too, like brake force, helps the driver to maintain and change the speed of the vehicle as per his wish and/or need. In this study, throttle pressure was measured in terms of acceleration values due to throttle. Figure 4 and Table 4 show the average acceleration of the vehicle due to braking in different types of segments (in terms of intersection separation distance or in other words intersection density) of the road.

Figure 4. Average acceleration of the vehicle due to throttle pressure in each distinct segment.

It can be observed that the average value of acceleration due to throttle is higher for segments with 100 m and 300 m intersection separation distance than that of the segment with 200 m intersection separation distance. However, from a more general point of view, along with the results shown in Figures 2 and 3, it can be seen that these segments (100 m and 300 m) also have higher deceleration values due to more use of braking than in the case of 200 m.

Table 4. Summary of the statistical tests done on average acceleration value of the vehicle in each segment.

Extra-Urban Segments	Test Statistic	*p* Value
Test of homogeneity of variances	11.72	0.00
ANOVA	15.53	0.00
Welch	21.59	0.00
Brown–Forsythe	21.02	0.00
Games–Howell	$p < 0.05$ for all pairs except two (100–200 m and 300–600 m)	
Village Segments	**Test Statistic**	***p* Value**
F test for variances	1.28	0.23
t test assuming unequal variances	0.29	0.39

The ANOVA test, Welch test, and Brown–Forsythe all returned *p* values of 0.00, implying that it is a statistically significant fact that the average throttle pressure values are not the same in different extra-urban segments with different intersection separation distance. Moreover, the *p* values from the Games–Howell test, which measures significance, show that there is a statistically significant difference among all the pairs, except the pairs of intersection separation distances of 100–200 m and 300–600 m. However, the *p* value corresponding to the 100–200 m pair was 0.068, which is very close to 0.05. The Games–Howell test is a conservative test protecting against the inflated risk of type I error. The *t* test done on the same pair returned *p* value of 0.007. Therefore, it can be said that there exists a fairly significant difference between the means of these two cases from a statistical point of view although as per the Games–Howell test, the difference is not significant at 0.05 level. This means that except for the pair of 300–600 m, the extra-urban segments with different intersection separation distance levels indeed have average throttle pressure values which are statistically significantly different from each other. Results from the *t* test show that the *p* values are much more than 0.05 and hence it can be concluded that there is no statistically significant difference between the average throttle pressure values between the segments within villages with different intersection separation distance levels. In other words, intersection separation distance or intersection density level does not influence the use of throttle to a statistically quantifiable extent in a rural road within a village driving ambience.

4. Discussion

4.1. Average Speed in Different Segments

The elaborations of the average speed demonstrate that segments with different intersection separation distances indeed have average speed values which are statistically significantly different from each other. Hence, intersection separation distance, or in other words intersection density level, influences the average speed levels in a roadway. Within the village, a similar trend is also shown. The average speed of the segment increases when the intersection separation distance increases. The average speeds in the village segments are almost the same as the allowed upper speed limit in the villages, i.e., 50 km/h. As the speed limit is already quite a bit lower than that of the extra-urban segments, the driver gets enough time to deal with a conflict situation (other vehicle entering or crossing the road from an intersection) when it arises and hence, he does not need to decrease the speed further. Results from *t* test for village segments show that *p* value is less than 0.05 and hence it can be concluded that there is a statistically significant difference between the average speed values between the segments within villages with different intersection separation distance levels. Therefore, it can be said that intersection separation distance, or in other words intersection density level, influences the average speed levels in a roadway in a village driving ambience.

It must be noted that the difference between the average speed levels for segment with intersection separation distance of 100 m and 300 m is slightly more (also with higher statistical significance level) in case of the extra-urban segments than in the village segments, perhaps due to the lower speed limits present within the village as explained before.

4.2. Average Deceleration Due to Applied Brakes

Similar to the extra-urban situation, inside the village as the intersection separation distance increases, the risk perception also gets lower, exemplified by the decrease in the average deceleration value. However, while comparing the deceleration values for the same intersection separation distance (among the extra urban and village situation), it can be seen that the values differ substantially for the case of 300 m, but not so much for 100 m. This is perhaps because since within the village the average speed of the vehicle is much lower than in extra-urban areas, the driver finds himself at enough of a temporal and spatial distance when a vehicle tries to enter the road in case of the 300 m intersection separation distance. Hence, he does not perceive the situation to be of high risk and does not apply pressure on the brakes most of the time. He rather deals with the situation often only by controlling the pressure on gas pedal. However, in the case of the 100 m intersection distance, the interval at which the possibility of a vehicle entering the road is very short and therefore even in a lower driving speed, the driver finds himself at a short temporal and spatial distance from the vehicle entering the road. In this situation, the driver perceives the situation to be of high risk and applies pressure on the brakes.

Generally, the brake pedal use reveals that the average deceleration due to braking is maximal in the case of 100 m intersection separation distance within the village. Perhaps this is because the driving ambience within a village is more of an enclosed pattern and it makes the driver also worried about colliding with other obstacles present within the scenario.

This finding is also confirmed by the brake pedal results. Therefore, it is possible to generalize that intersection distance or intersection density influences the use of brakes in a village driving environment.

4.3. Average Acceleration Due to Throttle

Concerning the average acceleration due to throttle, results demonstrate that when the distance between successive intersections is less (e.g., the case of 100 m), there are more chances of another vehicle joining the road from any of the intersections, thereby making the points of conflict appear in quicker succession. Thus, the driver has to take the pressure off the gas pedal and/or apply brakes more often as speed reduction is one of the most widely employed actions by drivers when they perceive any risk. Probably, in the 300 m intersections distance segments, the driver perceives the situation as less risky than the 200 m ones. Therefore, the driver puts more pressure on the gas pedal, but very soon, a potential conflict arises (sooner than in the case of 600 m) and he has to reduce speed by taking his foot off the gas pedal and/or by applying brakes to deal with the situation.

This results in a sudden dip in the speed and ultimately reduces the average speed and increases the average deceleration value.

Instead, in the segment with 200 m distance between the intersections, as the distance is shorter, the driver remains more alert to the potential risks and does not put so much pressure on the gas pedal. Therefore, the requirement of taking the foot off the gas pedal or applying brakes is less in this segment and therefore, there are fewer speed fluctuations than the case of 300 m. In other words, in this segment, speed fluctuation or the acceleration-deceleration behavior is less sporadic than the segment with intersection separation distance as 300 m. This causes an increase of average speed and a decrease of average deceleration value due to braking. Moreover, this acceleration-deceleration behavior, due to throttle pressure, leads to a higher average acceleration value in the cases of 100 m and 300 m than 200 m. In those two segments, drivers frequently felt the need to accelerate back to the previous level after decelerating due to perceived risks. However, even if the acceleration-deceleration pattern was more uniform in the case of 200 m, as vehicles were entering the roadway at closer intervals, the driver did not put higher pressure on the gas pedal due to perceived risk. The throttle pressure value for the segments with 300 m intersection distance was higher than that of 100 m. The intervals between the intersections were longer and hence, the driver could put relatively more pressure on the gas pedal.

For the segment with intersection separation distance of 600 m, the potential conflict points where other vehicles could join the road were quite substantially far from each other. Hence, the driver perceived this as a low-risk situation and put more pressure on the gas pedal without much use of the brakes or taking feet off the gas pedal. This results in higher average speed and average acceleration value due to throttle pressure and low average deceleration value in the segment. However, the difference between the average acceleration due to throttle pressure values corresponding to the case of 300 m and 600 m was less, albeit due to different reasons. In the case of 300 m, a good part of it was due to the need of accelerating back to the previous level after frequent deceleration due to perceived risks. Instead, in the case of 600 m intersection distance, the high average value of throttle pressure was mostly due to achieving higher speeds and not due to sporadic acceleration-deceleration pattern. It should be remembered that the speed limit for all of these segments was 90 kmph. However, due to other vehicles joining and leaving the road, the actual average speed of the driver's vehicle was much lower than 90 kmph as the driver perceived these events as potentially risky conflict points and dealt with the situation as such.

Finally, intersection separation distance or intersection density level influences the throttle pressure levels or pressure on gas pedal in a rural road.

In the case of the villages, the average acceleration due to throttle was slightly higher for the case of 100 m than 300 m, but the difference was less, probably due to the lower speed limit present within the village.

5. Speed Reduction and Risk Perception

When driver sees a vehicle entering the road in front of him, he assesses the situation and if he perceives it to be risky, he takes necessary action, most commonly by reducing speed. Departure from the trend for the driver performance measures in the extra-urban case of 300 m intersection separation distance was suspected to be stemming from different speed increment-reduction behavior present in this said case. Therefore, in order to further explore drivers' risk perception with regard to intersection separation distance and verify the suspected reason behind the aforementioned case of departure from trend, speed reduction counts, i.e., the number of time when speed was reduced in each of the extra-urban segments, were calculated. It must be noted that the numbers are not integers as the numbers were averaged for all the drivers and then normalized for the length of the segments as the total length of segments with different intersection density levels were not the same in the scenario. In fact, to have a significant and balanced number of cases with different intersection densities, it was necessary to adopt a system with different segment lengths. Therefore, the length of each group (100 m, 200 m, 300 m, and 600 m) was normalized with respect to the total length of each group of segments.

Figure 5 and Table 5 show the normalized values of these speed reduction counts and the related statistical test results.

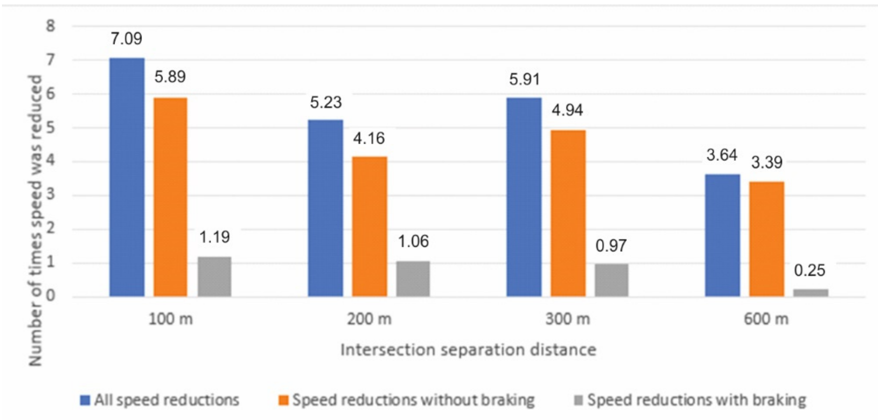

Figure 5. Speed reduction counts for each type of extra urban segment when normalized for length of the segments.

Table 5. Summary of the statistical tests done on the speed reduction counts in extra urban segment.

	All Speed Reductions		**Speed Reductions without Braking**		**Speed Reductions with Braking**	
	Test Statistic	***p* Value**	**Test Statistic**	***p* Value**	**Test Statistic**	***p* Value**
Test of homogeneity of variances	1.033	0.38	1.497	0.22	11.905	0.00
ANOVA	10.787	0.00	6.866	0.00	23.146	0.00
Welch	Not applicable		Not applicable		55.975	0.00
Brown–Forsythe	Not applicable		Not applicable		23.146	0.00
Tukey's HSD	$p < 0.05$ for all pairs		$p < 0.05$ for all pairs		Not applicable	
Games–Howell	Not applicable		Not applicable		$p < 0.05$ for all pairs	

As it can be seen from Figure 5, a departure from the trend was observed for all speed reduction counts in the extra-urban case of 300 m intersection separation distance. Therefore, it confirms that in the extra-urban case of 300 m intersection separation distance, indeed there were more sporadic speed fluctuations than in the case of 200 m, which resulted in departure from the trend for other driver performance measures such as average speed, brake force, and throttle pressure values. Furthermore, these speed reduction counts were explored in a more detailed way in terms of how these speed reductions were carried out. Speed reduction of a vehicle can be done just by reducing the pressure on the gas pedal or by putting pressure on the brake pedal in addition to that. Usually, the use of brake indicates that the driver perceived the situation to be riskier. Similarly, when drivers perceive a situation to be of lower risk, they reduce the speed of the vehicle just by reducing the pressure on the gas pedal. Figure 5 shows that the departure from the trend in the case of 300 m was present also for the speed reductions without braking counts. However, there was no departure from the trend for speed reduction with braking counts. Therefore, it is evident that some speed fluctuations do not depend on very high perceived risk that demands the use of brakes. It is probably due to the fact that in segments with higher intersection distance, drivers find conflict situations after relatively longer temporal gaps and therefore they get more time and distance to deal with such situations. This results in a lesser number of situations where drivers perceive the entrance of a vehicle from an intersection to be of such a high risk that demands the use of brakes to reduce the speed in order to avoid a potential collision. Results from Table 5 show that p values for the ANOVA, Welch, and Brown–Forsythe tests are less than 0.05. Therefore, it is a statistically significant fact that speed reduction counts are not the same in different types of extra-urban segments. Furthermore, the pairwise comparison tests, Tukey's HSD, and Games–Howell show that there is a statistically significant difference among all pairs. Therefore, it can be said that intersection density in a rural road influences the driver's risk perception as exemplified by the different speed reduction counts. In order to investigate further, the amount of brake force used for these speed reductions were explored. Figure 6 demonstrates the use of brake force for these speed reductions in each type of extra-urban segment.

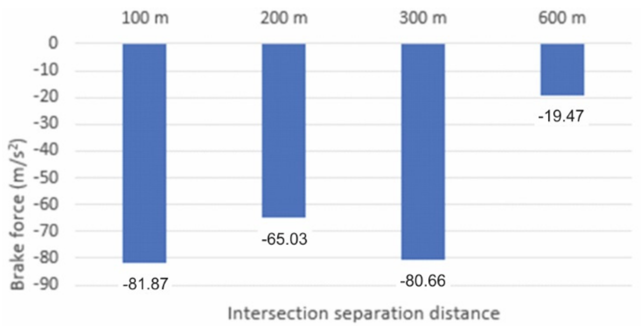

Figure 6. Total amount of brake force used for speed reductions after normalization for length of each type of extra-urban segment.

It is interesting to observe the results from Figure 6 not only individually, but together with Figures 3 and 5. Although the number of brakes used to reduce speed decreased with decreasing intersection density, in case of an intersection separation distance of 300 m, the total amount of brake force and average brake force values were a departure from a similar trend. Results from the ANOVA, Welch, and Brown–Forsythe test in this case reported p values as 0.00. The Games–Howell test results showed that differences in total brake force are significant at 0.05 level for all pairs except for the pair 100–300 m. This shows that for the extra-urban case of 300 m intersection distance, there is not only more sporadic speed fluctuation behavior than the case of 200 m, but also with relatively higher pressure on brakes.

6. Conclusions

This driving simulator study reveals interesting insights regarding the risk perception of drivers with respect to intersection density in a rural road. By and large, trends observed in all the driver performances suggested that with increasing intersection separation distance, or in other words decreasing intersection density, the driver's perceived risk gets lower and it results in higher average speed, lower brake usage, and more pressure on the gas pedal. This is in harmony with the findings of almost all the existing accident prediction modeling studies which suggest that with increase in intersection density, expected rates of accident occurrence also increase. However, for most of those measures, there was a departure from the trend for the extra-urban mid-level intersection separation distance of 300 m. The reason behind this departure is more sporadic speed fluctuation behavior than its neighboring cases. This was confirmed by multiple driver performance data in this study, but most convincingly by the relatively higher speed reduction count and total brake force used for speed reductions for the case of 300 m. Higher speed fluctuations indicate an oscillating risk perception among drivers in the mid-level intersection density. These oscillations in risk perception can be dangerous and potentially lead to an accident if the driver fails to perceive the actual risk that is present. In this context, it is worth mentioning that the Road Safety Manual (RSM) mentions that for a vehicle travelling at 100 km/h, the distance covered before the vehicle can be brought to a complete stop may be up to 300 m instead of the lower stopping distance suggested by the many current guidelines. In future, on-field experiments with connected vehicles could reveal more insights regarding the effect of intersection density on drivers' risk perception in the real world. To conclude, based on the results of this driving study, it can be said that there exists a positive co-relation between intersection density and drivers' risk perception in rural roads. At the same time, attention should be paid to the rural road segments with mid-level intersection density. Since accessibility and mobility are both important, concepts such as access consolidation may be utilized in this regard. Beyond the domain of accident research, from a practical application point of view, findings from this study can also be useful for engineers, transportation agencies, and other stakeholders associated with access management to help them make more informed decisions.

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